MIE334 - Numerical Methods I

Lecture 32: ODEs and Euler Method (C&C 25.1)

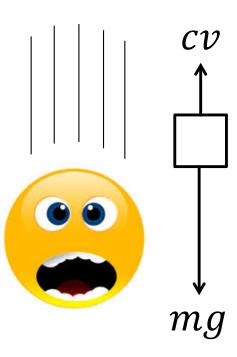
Roadmap: C&C Part Seven

- Integration of ODEs (C&C 25)
 - Euler's Method (25.1)
 - Heun's Method (25.2)
 - Runge-Kutta Methods (25.3)
 - Systems of Equations (25.4)

Differential equation:

$$F = ma$$

$$mg - cv = m\frac{dv}{dt}$$



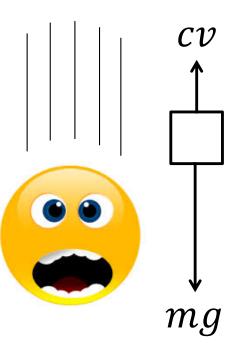
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Rewriting:

$$\frac{dv}{dt} = g - \frac{c}{m}v$$



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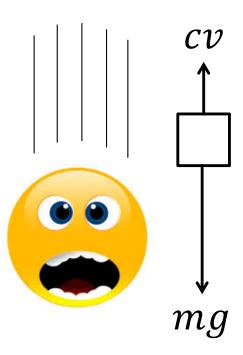
$$mg - cv = m\frac{dv}{dt}$$

Rewriting:

$$\frac{dv}{dt} = g - \frac{c}{m}v$$

• Solution (for v = 0 at t = 0):

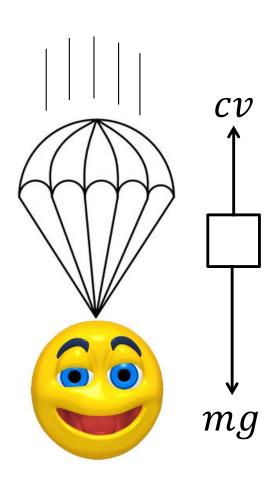
$$v = \frac{mg}{c} \left(1 - e^{-(c/m)t} \right)$$



Application:

$$v = \frac{mg}{c} \left(1 - e^{-(c/m)t} \right)$$

Design c for a prescribed velocity



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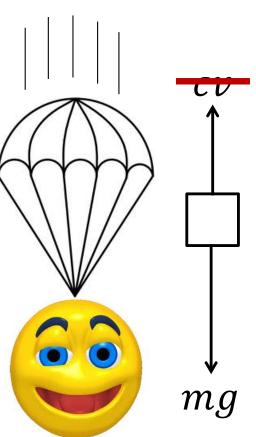
$$v = \frac{mg}{c} \left(1 - e^{-(c/m)t} \right)$$

- Design c for a prescribed velocity
- What if relationship was more complex?

$$\frac{dv}{dt} = g - \frac{c}{m} \left[v + d \left(\frac{v}{v_{max}} \right)^e \right]$$

• where d, e, and v_{max} are empirical constants

$$c\left[v+d\left(\frac{v}{v_{max}}\right)^{e}\right]$$



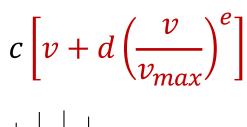
Application:

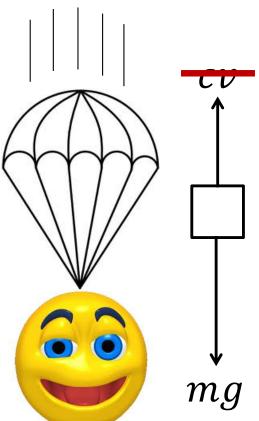
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- where d, e, and v_{max} are empirical constants
- More difficult to solve analytically
 - Need numerical methods to solve v(t)





- Ordinary Differential Equations (ODE):
 - Involves one independent variable (here, t):

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Slide 9

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- 1st order: Highest derivative is 1st derivative
- nth order: Highest derivative is nth derivative
- Can convert nth order ODE to n first-order ODEs!
 - Later...

First-order ODEs

Focus on first-order ODEs of the form:

$$\frac{dy}{dx} = f(x, y)$$
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$$y = y(x)$$

Given only the following:

$$y_0 = y(x_0)$$

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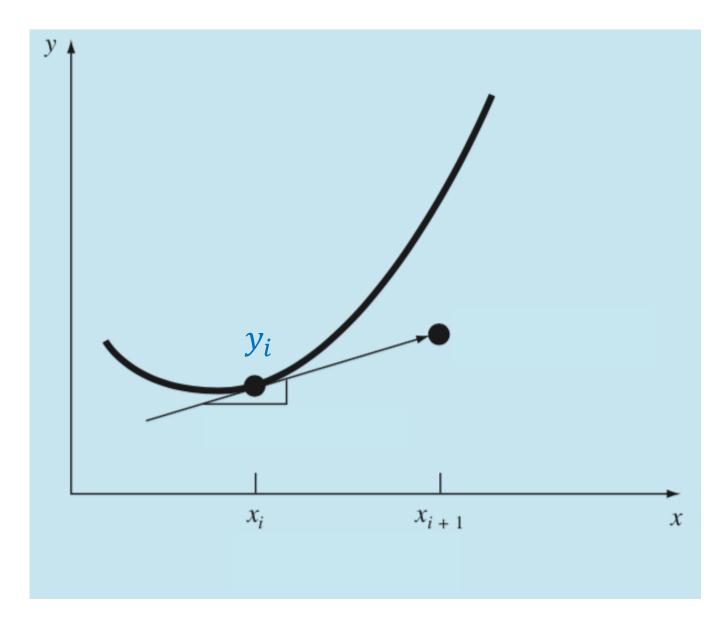
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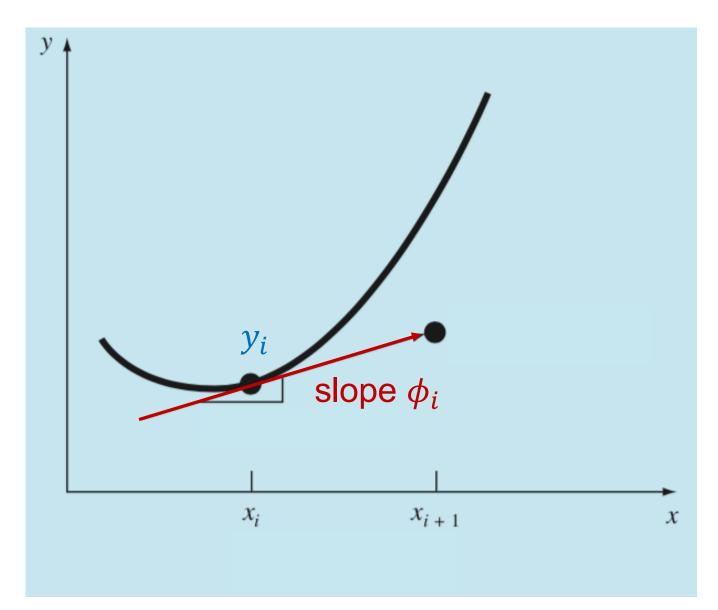
$$y_0 = y(x_0)$$

- First-order ODEs only have one boundary condition
 - Sometimes called initial condition, especially for problems in time

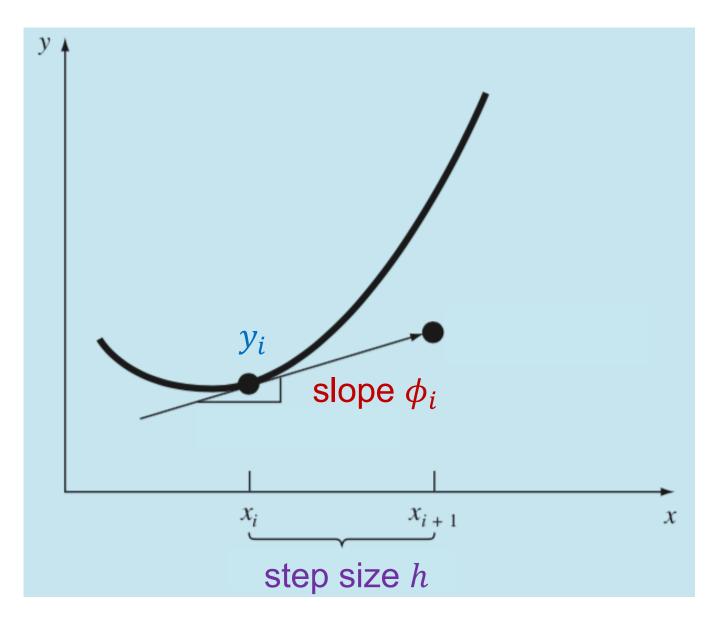
1) Start at $y(x_i) \equiv y_i$



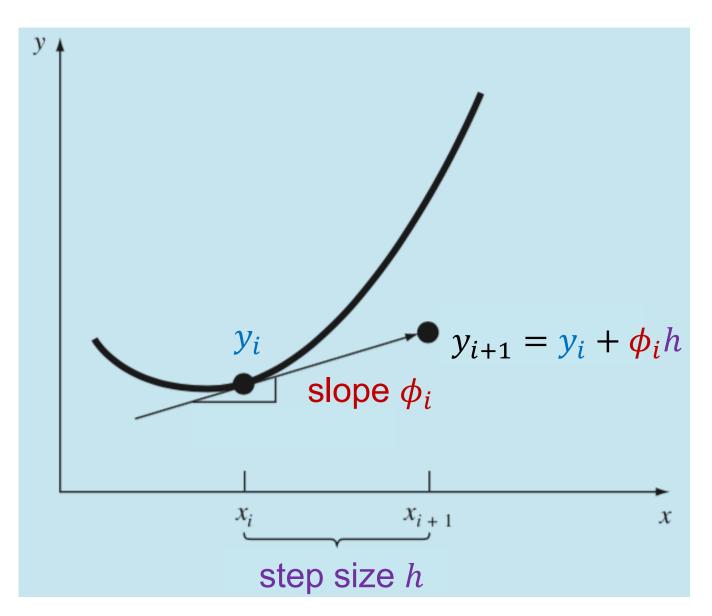
- 1) Start at $y(x_i) \equiv y_i$
- 2) Estimate slope ϕ_i



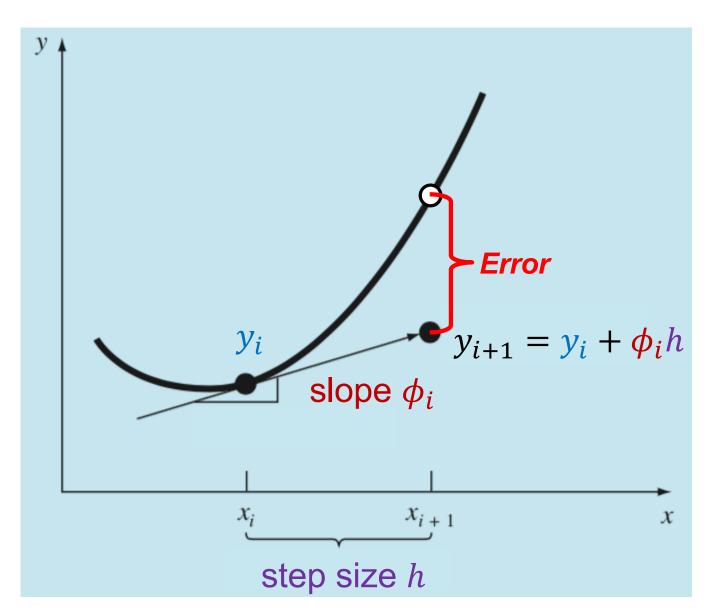
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- 3) Take step of size *h*



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• Accuracy of y_{i+1} obviously depends heavily on the choice of slope

$$\phi_i = \frac{y_{i+1} - y_i}{h}$$

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- These are the Runge-Kutta (RK) family of methods
 - Will start with Euler's Method, the simplest
 - Will build towards 4th-order RK, the most popular

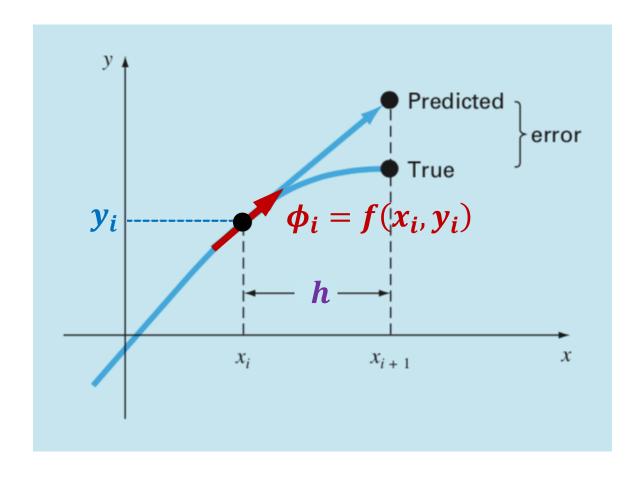
Simplest RK: Euler's Method

Governing ODE:

$$y' = f(x, y)$$

• Set ϕ = slope at i:

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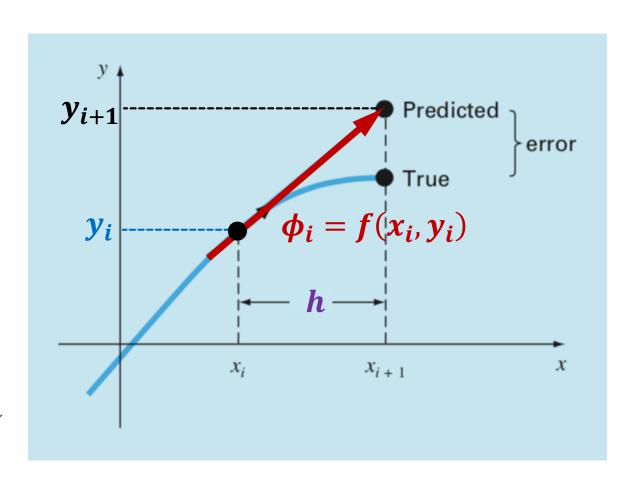
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Euler predictor:

$$y_{i+1} = y_i + \phi_i h$$

= $y_i + f(x_i, y_i) h$



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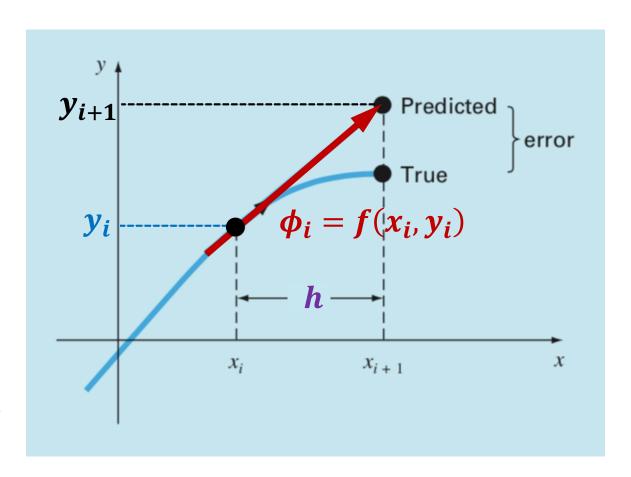
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Smarter methods later, called predictor-corrector

• Solve for y(x) using Euler's Method:

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- f(x,y) is a simple polynomial, so true solution available for error calculation:

$$y(x) = 0.5x^4 + 4x^3 - 10x^2 + 8.5x + 1$$

$$y' = -2x^3 + 12x^2 - 20x + 8.5$$
 $y(0) = 1$

Initial condition (i = 0)

$$x_i = x_0 = 0$$
$$y(x_0) = y_0 = 1$$

$$y' = -2x^3 + 12x^2 - 20x + 8.5$$
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• Initial condition (i = 0)

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• Estimate slope $\phi_i = f(x_i, y_i) [= y_i']$ $\phi_0 = f(x_0, y_0)$

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Euler Example: Results (h=0.5)

	i	x_i	y_i
Initial condition →	0	0.0	1.00000
	1	0.5	5.25000
	2	1.0	5.87500
	3	1.5	5.12500
Estimates of $y(x)$	4	2.0	4.50000
for each x step	5	2.5	4.75000
	6	3.0	5.87500
	7	3.5	7.12500
	8	4.0	7.00000

Euler Example: Results (h=0.5)

	l	x_i	y_i	Ytrue	\mathcal{E}_t [%]
Initial condition →	0	0.0	1.00000	1.00000	-
	1	0.5	5.25000	3.21875	63%
	2	1.0	5.87500	3.00000	96%
	3	1.5	5.12500	2.21875	131%
Estimates of $y(x)$	4	2.0	4.50000	2.00000	125%
for each x step	5	2.5	4.75000	2.71875	75%
	6	3.0	5.87500	4.00000	47%
	7	3.5	7.12500	4.71875	51%

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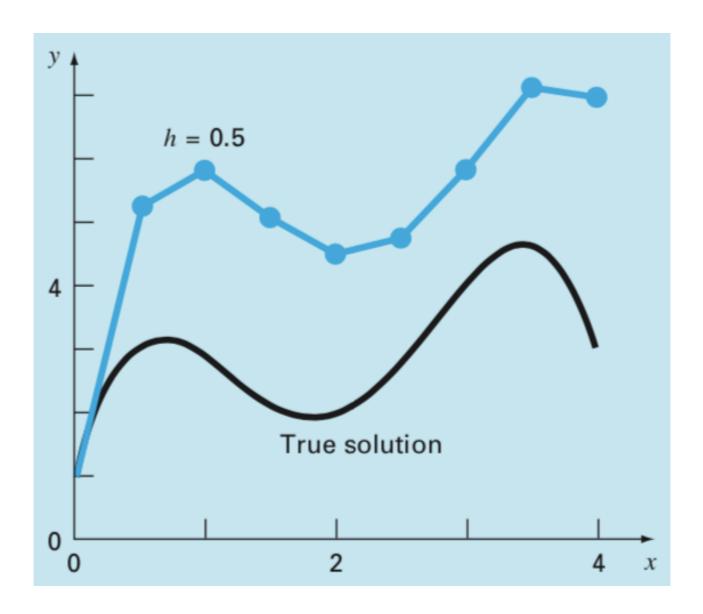
7.00000

3.00000

133%

4.0

Euler Example: Results (h=0.5)



Poll Question

How could we improve upon the results we just got?

- 2) Use higher-order approximation for y_i'
- 3) Use better estimate of slope ϕ_i
- 4) Use backward difference approximation for y'_i

$$y_i' \cong \frac{y_{i+1} - y_i}{h} = \phi_i$$
$$y_{i+1} = y_i + \phi_i h$$

Consider Taylor Series:

$$y_{i+1} = y_i + y_i'h + \frac{y_i''h^2}{2!} + \frac{y_i'''h^3}{3!} + \cdots$$

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- So error for Euler's Method should be $O(h^2)$
 - If we reduce h by factor of 2, error should drop 4x...

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$$= y_i + f(x_i, y_i)h + O(h^2)$$

- So error for Euler's Method should be $O(h^2)$
 - If we reduce h by factor of 2, error should drop 4x...
- Try h = 0.25 instead of h = 0.5
 - See MIE334_Lecture_32_ExEuler.xlsx

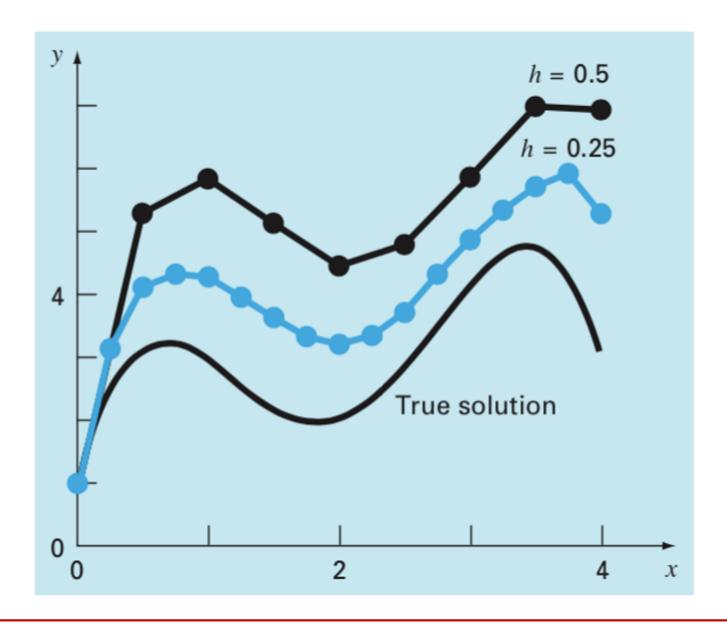
Euler Example: Results (h=0.25 vs. h=0.5)

i	x_i	y_i	<i>y_{true}</i> (h=0.25)	$arepsilon_t [\%] \ ag{h=0.25}$	$arepsilon_t [\%] \ ext{(h=0.5)}$
0	0.0	1.00000	1.00000	-	-
2	0.5	4.17969	3.21875	30%	63%
4	1.0	4.34375	3.00000	45%	96%
6	1.5	3.55469	2.21875	60%	131%
8	2.0	3.12500	2.00000	56%	125%
10	2.5	3.61719	2.71875	33%	75%
12	3.0	4.84375	4.00000	21%	47%
14	3.5	5.86719	4.71875	24%	51%
16	4.0	5.00000	3.00000	67%	133%

Euler Example: Results (h=0.25 vs. h=0.5)

i	x_i	y_i	<i>y_{true}</i> (h=0.25)	$arepsilon_t [\%] \ ext{(h=0.25)}$	$arepsilon_t [\%] \ ext{(h=0.5)}$	Error Drop
0	0.0	1.00000	1.00000	_	-	
2	0.5	4.17969	3.21875	30%	63%	2.1x
4	1.0	4.34375	3.00000	45%	96%	2.1x
6	1.5	3.55469	2.21875	60%	131%	2.2x
8	2.0	3.12500	2.00000	56%	125%	2.2x
10	2.5	3.61719	2.71875	33%	75%	2.3x
12	3.0	4.84375	4.00000	21%	47%	2.2x
14	3.5	5.86719	4.71875	24%	51%	2.1x
16	4.0	5.00000	3.00000	67%	133%	2.0x

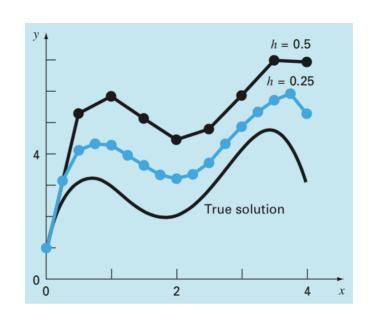
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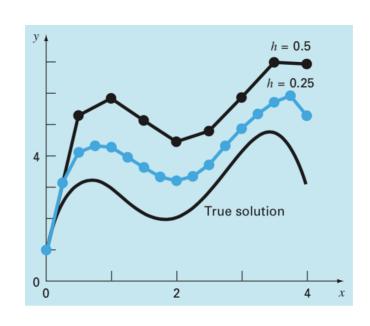
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 - Roundoff: finite precision (# of significant digits) in the representation of numbers

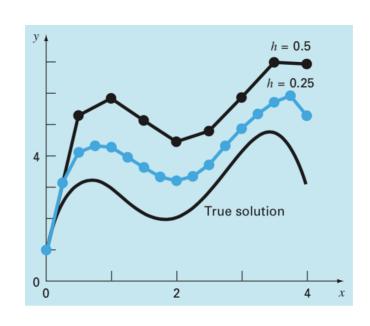
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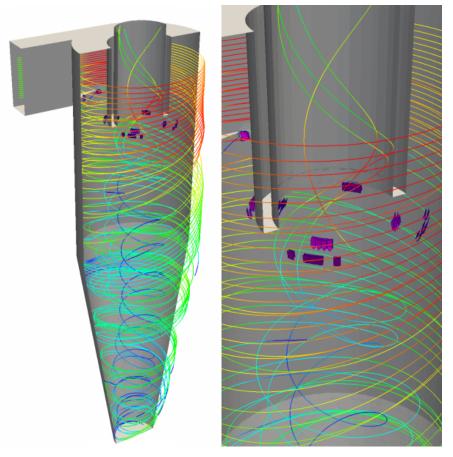
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 - Sum is the Global truncation error



CFD Particle Tracking: Global Error

- Velocity is a (time-varying) vector:
 - $\{u(t), v(t), w(t)\}$
- Compute pathlines by integrating each velocity component from initial "seed" locations:

$$dx/dt = u(x, y, z, t)$$
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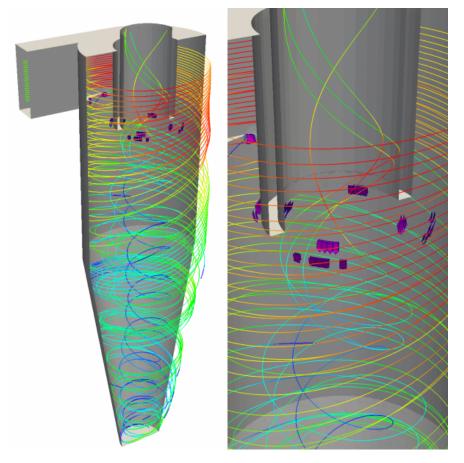


https://cfd.direct/openfoam/free-software/barycentric-tracking/

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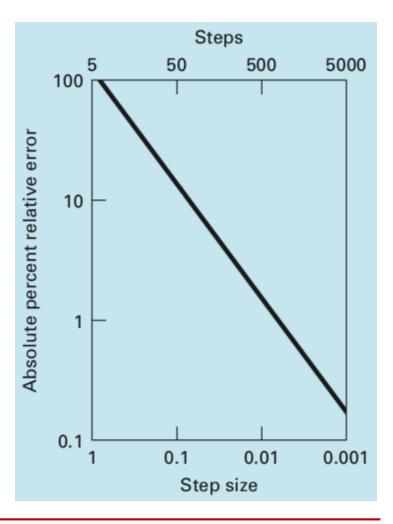
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Later will discuss numerical solution of multiple ODEs

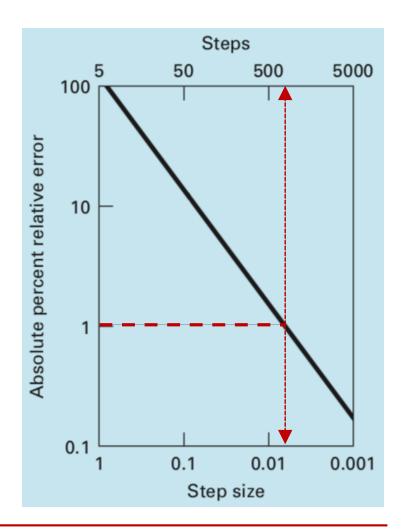
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- For $\varepsilon_s = 1.0\%$, would need more than 500 steps (h < 0.01)!



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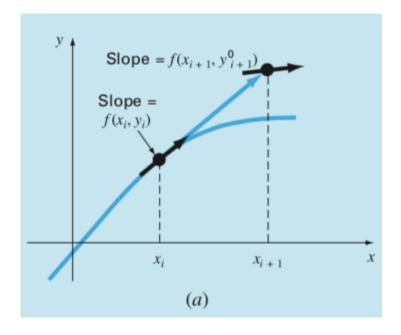
- Still needs to start with Euler method
 - Propagated error
- Still relies on slope from previous step
 - Local error
 - Clever ways around this (C&C 26, will skip)

Higher-order Methods: Single step

 Improve the estimation of the slope over the interval by using more than one estimate of the slope

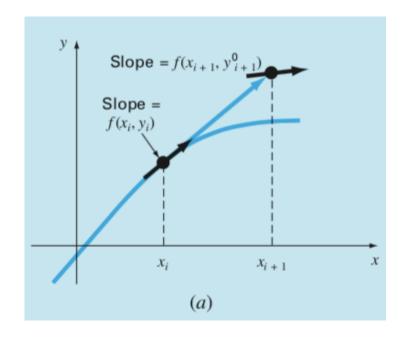
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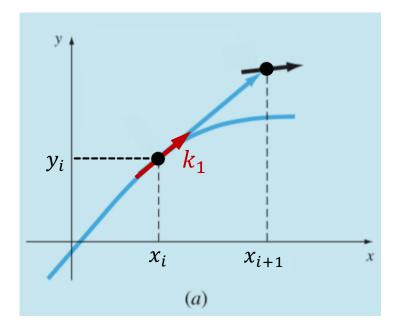
- Improve the estimation of the slope over the interval by using more than one estimate of the slope
- Heun's Method:
 - One at the start, one at the end



- Other methods later:
 - Different and/or more locations for slope estimation

1) Slope at start (x_i)

$$\mathbf{k_1} = f(x_i, y_i)$$

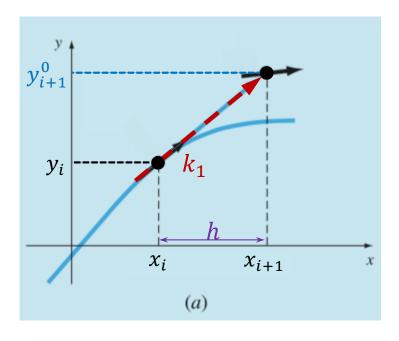


1) Slope at start (x_i) :

$$\mathbf{k_1} = f(x_i, y_i)$$

2) Predictor (Euler):

$$y_{i+1}^0 = y_i + k_1 h$$

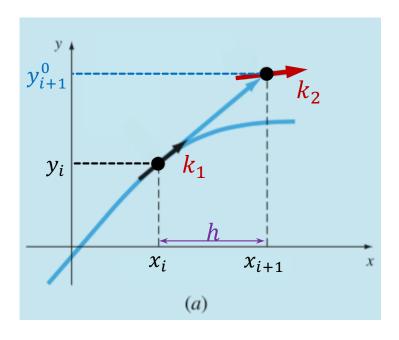


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3) Slope at end (x_{i+1}) : $k_2 = f(x_{i+1}, y_{i+1}^0)$



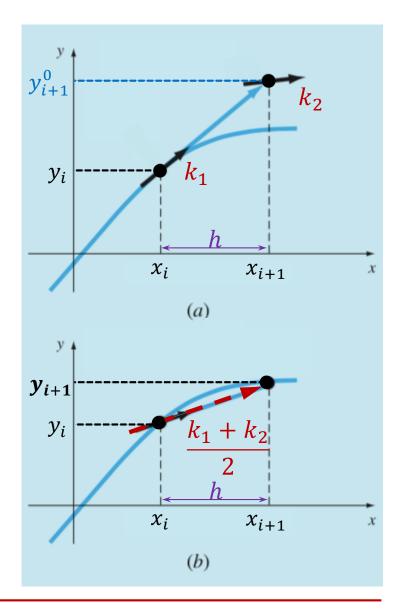
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- 3) Slope at end (x_{i+1}) : $k_2 = f(x_{i+1}, y_{i+1}^0)$
- 4) Corrector:

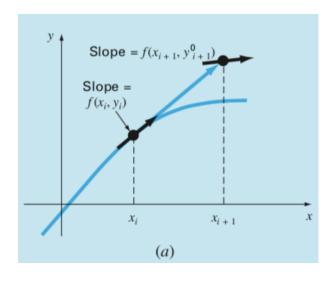
$$\mathbf{y_{i+1}} = y_i + \left(\frac{k_1 + k_2}{2}\right)h$$



$$y' = -2x^3 + 12x^2 - 20x + 8.5$$
 $y(0) = 1$

Predictor:

$$k_1 = f(x_0, y_0) = f(0,1) = 8.5$$

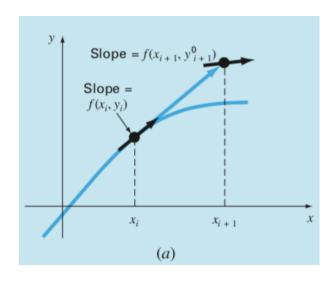


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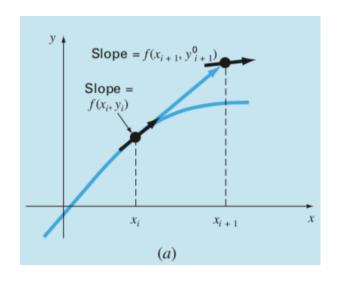


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 $x_1 = x_0 + h = 0 + 0.5 = 0.5$



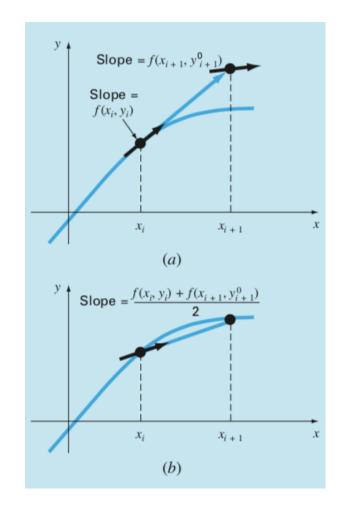
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 $x_1 = x_0 + h = 0 + 0.5 = 0.5$

$$k_2 = f(x_1, y_1^0) = f(0.5, 5.25) = 1.25$$



$$y' = -2x^3 + 12x^2 - 20x + 8.5$$
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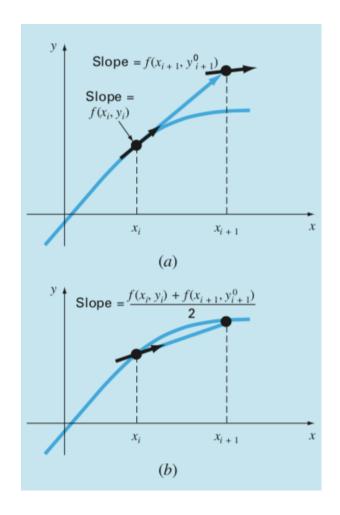
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$$k_2 = f(x_1, y_1^0) = f(0.5, 5.25) = 1.25$$

 $y_1 = y_0 + \left(\frac{k_1 + k_2}{2}\right)h$



$$y' = -2x^3 + 12x^2 - 20x + 8.5$$
 $y(0) = 1$

Predictor:

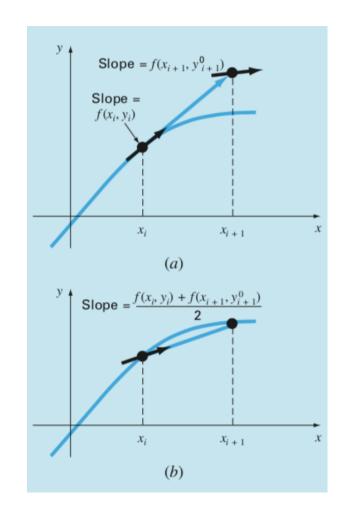
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$$y_1 = y_0 + \left(\frac{k_1 + k_2}{2}\right)h$$

$$= 1 + \left(\frac{8.5 + 1.25}{2}\right)(0.5) = 3.4375$$



Heun Example: Second step (h=0.5)

$$y' = -2x^3 + 12x^2 - 20x + 8.5$$
 $y(0) = 1$

Predictor:

$$k_1 = f(x_1, y_1) = f(0.5, 3.4375) = 1.25$$

 $y_2^0 = y_1 + k_1 h = 3.4375 + (1.25)(0.5) = 4.0625$
 $x_2 = x_1 + h = 0.5 + 0.5 = 1.0$

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 $y_2^0 = y_1 + k_1 h = 3.4375 + (1.25)(0.5) = 4.0625$
 $x_2 = x_1 + h = 0.5 + 0.5 = 1.0$

$$k_2 = f(x_2, y_2^0) = f(1.0, 4.0625) = -1.5$$

$$y_2 = y_1 + \left(\frac{k_1 + k_2}{2}\right)h$$

$$= 3.4375 + \left(\frac{1.25 + (-1.5)}{2}\right)(0.5) = 3.375$$

Heun Example: Results (h=0.5)

i	x_i	УHeun	$ arepsilon_t $ [%]
0	0.0	1	-
1	0.5	3.43750	7%
2	1.0	3.37500	13%
3	1.5	2.68750	21%
4	2.0	2.50000	25%
5	2.5	3.18750	17%
6	3.0	4.37500	9%
7	3.5	4.93750	5%
8	4.0	3.00000	0%

Heun Example: Results vs. Euler (h=0.5)

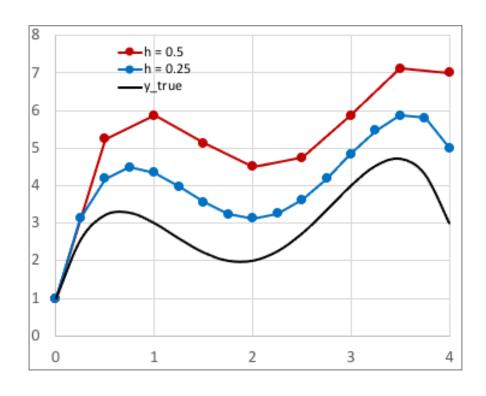
i	x_i	Унеип	$ arepsilon_t $ [%]	Y Euler	$ arepsilon_t $ [%]
0	0.0	1	-	1.00000	-
1	0.5	3.43750	7%	5.25000	63%
2	1.0	3.37500	13%	5.87500	96%
3	1.5	2.68750	21%	5.12500	131%
4	2.0	2.50000	25%	4.50000	125%
5	2.5	3.18750	17%	4.75000	75%
6	3.0	4.37500	9%	5.87500	47%
7	3.5	4.93750	5%	7.12500	51%
8	4.0	3.00000	0%	7.00000	133%

Heun Example: Results vs. Euler (h=0.5)

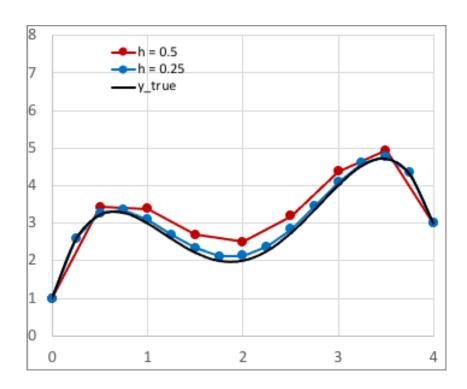
i	x_i	Унеип	$ arepsilon_t $ [%]	Y Euler	$ arepsilon_t $ [%]	Error Drop
0	0.0	1	-	1.00000	-	-
1	0.5	3.43750	7%	5.25000	63%	9.0x
2	1.0	3.37500	13%	5.87500	96%	7.4x
3	1.5	2.68750	21%	5.12500	131%	6.2x
4	2.0	2.50000	25%	4.50000	125%	5.0x
5	2.5	3.18750	17%	4.75000	75%	4.4x
6	3.0	4.37500	9%	5.87500	47%	5.2x
7	3.5	4.93750	5%	7.12500	51%	10x
8	4.0	3.00000	0%	7.00000	133%	N/A

Heun Example: Results vs. Euler

Euler's Method



Heun's Method



MIE334_Lecture_32_ExEuler.xlsx

MIE334_Lecture_32_ExHeun.xlsx

Poll Question

For Heun's Method, the error at x=4 is 0%. Does that mean there would be no more error if were to continue taking steps **past** x=4?

- 1) Yes
- 2) No